Retrospective Cohort Study of Factors Impacting Client Attendance in Physical Rehabilitation Clinics

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Abstract. *In an environment of high client demand and provider shortages, missed appointments trouble rehabilitation clinic managers because they reduce the number of appointment slots used to serve clients. The attendance prediction models reviewed require time intensive data collection and many have low predictive power. Rehabilitation administrators need practical models for the prediction of missed appointments so that they can successfully develop and implement intervention strategies. In this retrospective cohort study, client non-attendance is analyzed in the specialty of physical rehabilitation, where multiple appointments may occur in a relatively short period of time. Five types of currently available data were collected from over 4,000 active client charts at three clinic health systems with a total of ten local ambulatory clinic facilities for physical rehabilitation. Multiple regression analysis showed that the four predictors—age group, payment method, proximity to clinic, and attendance history—significantly explain slightly more than a third of client attendance variability.*

Access and availability are important components of client satisfaction with medical services (Khalil & Sufi, 2009; Klegon, Gregory, & Kingstrom, 1982; Kovner & Smits, 1978). Some medical specialties, such as physical rehabilitation, are projected to experience shortages in the near future (Economic Modeling Specialists, 2010; Shanahan, 1993). Despite high job satisfaction among physical therapists, both hospital and ambulatory clinic administrators face shortages of physical therapists (Atwood & Woolf, 1982; Economic Modeling Specialists, 2010; Ogulata, Koyuncu, & Karakas, 2008; Shanahan, 1993). This mismatch between supply and demand is further complicated by high numbers of missed physical rehabilitation appointments. In an environment of client demand and provider shortages, missed appointments trouble clinic managers because they reduce the number of appointment slots used to serve clients. For example, if an ambulatory clinic with 8,000 appointment slots per year experiences a 20% missed appointment rate, then the therapists within the clinic lose 1,600 opportunities to treat clients. Today's rehabilitation providers

face significant challenges to improve client access to high quality care (Otani, Kurz, Burroughs, & Waterman, 2003).

It is clearly of interest to clinic managers to discover if missed appointments occur in a random fashion or if particular types of clients are more likely to miss appointments. If a simple schema can be developed to identify those clients with a high probability of failure to meet scheduled appointments, then greater efforts to encourage attendance can be directed toward those "high risk" clients. A targeted approach to encourage schedule compliance may be more efficient than a "blanket" approach, wherein efforts to encourage attendance are directed at all clients, even those with a high probability of meeting scheduled appointments.

As is true of most rehabilitation clinics, missed appointments impact ambulatory clinics. For example, in past studies the percentage of primary care missed appointments has been reported to be as high as 55% (Vikander et al., 1986) and 64% (Starkenburg, Rosner, & Crowley, 1988). The percentage of rehabilitation clients missing at least one appointment has been reported to be as high as 41% (Worsfold, Langridge, Spalding, & Mullee, 1996) and 46% (Bishop, Meuleman, Robinson, & Light, 2007). Clearly, clinic managers' concerns about client non-attendance are confirmed by the data.

Rehabilitation clinic managers have instituted various responses to client non-attendance. For example, managers may adopt double-booking scheduling strategies (Kros, Dellana, & West, 2009; LaGranga & Lawrence, 2007); however, if waiting time is increased, then client satisfaction may decrease (Klegon et al., 1982; Kovner & Smits, 1978; Zhu, Heng, & Teow, 2012). Other clinic administrators may convert to short-notice scheduling strategies because they have been shown to reduce the number of missed appointments (Qu, Rardin, Williams, & Willis, 2007; Quinn, 2007). Clinic administrators have also used appointment reminder systems to reduce the likelihood that a client forgets an appointment (Collins, Santamaria, & Clayton, 2003; Hashim, Franks, & Fiscella, 2001; Macharia, Leon, Rowe, Stephenson, & Haynes, 1992; Quinn, 2007; Vasey, 1990). Despite new scheduling and reminder systems, client non-attendance continues to impact clinic operations (Parikh et al., 2010; Quinn, 2007).

A statistical model to determine the relationship between client non-attendance and various individual-level factors may assist clinic administrators to identify clients who might need extra reminders or other intervention measures. Despite various client attendance prediction models in the literature (Bean & Talaga, 1995; Brewer et al., 2000; Dove & Schneider, 1981; Goldman, Freidin, Cook, Eigner, & Grich, 1982; Grindley, Zizzi, & Nasypany, 2008; Gruzd, Shear, & Rodney, 1986; Lagerlund, Hedin, Sparén, Thurfjell, & Lambe, 2000; Lee, Earnest, Chen, & Krishnan, 2005; Neal et al., 2001; Norman & Conner, 1996; Qu et al., 2006; Smith & Yawn, 1994), none have been widely implemented due to either their requirements for data not easily accessed or their lack of statistical significance. While factors such as gender, age, race, marital status, payment method, type of care, and past attendance history are readily available in traditional or electronic medical records, other types of data included in many of the client prediction models reviewed are not. For example, some prediction models included data regarding distance from residence to clinic (Lee et al., 2005; Smith & Yawn, 1994), the time between scheduling the appointment and the actual appointment (Bean & Talaga, 1995; Dove & Schneider, 1981; Lee et al., 2005), weather information (Qu et al., 2006), Townsend deprivation (poverty-related) scores based on census data (Neal et al., 2001), and physician identified psychosocial problems (Goldman et al., 1982). These last five variables are not routinely recorded in client charts and as a result would be difficult for clinic personnel to obtain.

Some attendance prediction models utilized data that could only be obtained through use of client questionnaires. For example, factors influencing client motivation were determined using various instruments, including instruments related to the Theory of Planned Behavior (Norman & Conner, 1996), assessments appropriate to the Protection Motivation Theory (Grindley, Zizzi, & Nasypany, 2008), or Self Motivation Inventory (Brewer et al., 2000). Similarly, as an alternative approach to predicting attendance, questions from the Health Belief Model were used to determine perceived barriers and benefits (Lagerlund et al., 2000), while another system used client questionnaires to determine perceptions related to cost of care (Gruzd et al., 1986). One model used input from a physician questionnaire based on the Facilitating Response Index (Gruzd et al., 1986). Such invasive and time-consuming techniques do not offer pragmatic direction to a clinic manager desiring

to reduce non-attendance. Finally, several authors reported that their attendance models were "not statistically significant" (Brewer et al., 2000) or had R^2 values less than 10% (Grindley et al., 2008; Lagerlund et al., 2000; Norman & Conner, 1996), once again offering little practical value for the clinic manager.

An important gap in management tools is a practical but powerful client attendance model based on data that are regularly collected by the clinic. Given the concerns that are expressed with respect to disclosure of personal information (Margulis, 2003; Rohm & Milne, 2004) and the inherent difficulty of data collection, it is important to develop a simple prediction model predicated upon routinely collected client information. It is not feasible to burden clinic personnel with requirements to extract and record additional information for prediction of attendance. By the same token, complex mathematical models are unlikely to be valued or utilized by clinic personnel. Yet clinic personnel are in need of a tool to predict client attendance behavior. For this reason, a retrospective cohort study was undertaken to determine if data routinely collected and available in client records could be used to predict client non-attendance for physical rehabilitation at local ambulatory clinics.

The variables selected for this study were based on important factors identified in previous studies as well as the availability of data in clinics. For example, age group has been identified as an important factor in previous studies of client attendance with several studies using age groups that include ranges of 30 or more years (Bean & Talaga, 1995; Brookes, 1992; Grindley et al., 2008). In this study, age group is utilized as a proxy for involvement in paid employment. Generally, individuals under age 16 are not engaged in full-time paid work activities. Since age 65 is still considered the traditional retirement age, involvement in paid work activities should decrease after age 65. Thus, for these two groups, work activities should be less likely to interfere with scheduling.

Similarly, previous research into client satisfaction indicates the importance of variables such as access to and cost of treatment (Klegon et al., 1982; Kovner & Smits, 1978; Rose & Chung, 2003). Studies have identified transportation access as a factor impacting client attendance (Brookes, 1992; Gleeson, Chant, Cusick, Dickson, & Hodgers, 1991; Vasey, 1990; Worsfold et al., 1996). Comparison of zip codes for the clinic and the client home address reflects travel distance, a proxy for transportation access.

Some research indicates that payment source may impact appointment attendance, (Davis, Estess, Simonton, & Bonda, 1977; Grindley & Zizzi, 2005) while at least one study suggests the absence of influence on client attendance (Kolt & McEvoy, 2003). Payment source, including private insurance or workers' compensation, serves as a proxy for cost of care, given the clear implications for cost to the client. We suggest that clients with a third-party payer are more likely to miss scheduled appointments due to a less salient cost to the client and subsequently lower motivation to keep scheduled appointments.

Finally, data on the number of kept and missed appointments are included in this model. Although treatment must be initiated in order for this information to be useful, attendance is routinely noted in client charts once treatment has begun. Previous attendance behavior, once available, serves as an important indicator of client behavioral tendencies. Thus, a client who has failed to keep an appointment in the past is less likely to keep other scheduled appointments.

In this study, client non-attendance is analyzed in the specialty of physical rehabilitation, where multiple appointments may occur in a relatively short period of time. A simple but effective tool for predicting client attendance behavior is crucial in such a setting because multiple missed appointments in a short time span can trouble staff and wreak havoc with the overall clinic schedule, thus reducing the level of service that the facility is able to provide and the facility's overall efficiency (Williams, Pepper, Webb, & Day, 2009). The following hypothesis is offered for this research:

> *Hypothesis 1. Client attendance is influenced by (a) age group, such that younger and older clients are more likely to attend; (b) payment source, such that clients with third party payers are less likely to attend; (c) zip code match, such that clients living in a different zip code than the clinic are less likely to attend; and (d) previous missed rehabilitation sessions, such that previous non-attendance is positively associated with later non-attendance.*

Method

Participants in the study ($n = 4,478$) were clients with active charts available in file cabinets or electronic medical records on the day of data collection at physical rehabilitation clinics managed by Baptist Health Care, Sacred Heart Health System, or West Florida

Healthcare. Typically, data were collected in one to two days with the exception of one large facility that required multiple days. The Institutional Review Board at the primary investigator's employer as well as those of the three participating organizations approved historic data collection and analysis without individual identifiers. The total number of active charts reviewed was 4,478, which represented most of the active clients during the data collection period. The sample was randomly split, with 80% ($n = 3,582$) of the observations used for model development. The model development sample size of 3,582 far exceeded the 1,000 required from a power calculation, assuming a confidence level of 0.99 and an R^2 of at least 2% (Hair, Black, Babin, Anderson, & Tatham, 2006). The remaining 20% of the sample ($n = 896$) was held out for cross-validation purposes.

Using a laptop computer and Microsoft Excel software, data from paper or electronic client documents were initially entered in alphabetical order of the client last name. The data were entered into a spreadsheet without any client identifiers. Then the data recorder double-checked the data at the initial entry. After all of the individual client's data were recorded in the spreadsheet and double-checked, all entries were randomly reordered to prevent later identification of clients as a result of the alphabetical sequencing of the entries. This procedure was completed each time a new entry was made.

Data collection included five variables:

1) Age group (<16 years of age, 16-64 years of age, 65 years of age)

2) Payment source (workers' compensation, private insurance, other)

3) Zip code match for physical rehabilitation clinic and client home address (yes/no)

4) Number of missed appointments

5) Number of kept appointments

Age group was coded as "1" for individuals between 16 and 64 years of age, inclusive, and "0" otherwise. Payment source was coded as "1" for private insurance or workers' compensation and "0" otherwise, given that only 3% of clients ($n = 150$) were covered by workers' compensation. Clients 65 years old or older who were covered by both Medicare and private insurance were coded as having private insurance. Zip code match was coded as "1" if the client's home address zip code matched that of the clinic and "0" otherwise. With respect to missed appointments,

only those missed appointments that were noted in the chart were included. Cancelled appointments, although recognized as potentially problematic, were not considered in this study, as they were less challenging to the clinic's schedule than missed appointments. Finally, the number of kept appointments was converted to a percentage for analytic purposes.

The developmental sample was analyzed using stepwise multiple regression. The dependent variable was percentage of appointments kept. Age group, payment source, zip code match, and number of missed appointments served as the independent variables. The regression equation computed in the developmental (80%) sample was then subjected to cross-validation in the 20% hold out sample. That is, a new variable was created in the hold out sample by utilizing the regression weights obtained in the developmental sample to compute a new variable that represented the predicted percentage of kept appointments. The actual percentage of kept appointments was then regressed on the predicted percentage of kept appointments in the hold out sample in order to obtain a cross-validated R^2.

Results

The characteristics of the data pool are summarized in Table 1 in terms of the age groups, comparison of client and clinic zip codes, payment sources, and history of kept and missed appointments. Utilizing the information from Table 1, it is interesting to consider the impact of client non-attendance on efficiency loss. The data collected revealed 9,790 missed appointments compared to 44,888 appointments attended. Efficiency is calculated as the ratio of the actual number of clients served versus the number of clients that could have been served. The number of unscheduled appointment slots is unknown for the ten clinic facilities over the data collection period. However, at least 9,790 appointment slots were unused due to missed appointments. Assuming no unscheduled appointment slots, the maximum efficiency loss is shown in Equation 1. Equation 1 shows that client non-attendance lowered efficiency by as much as 17.9%.

$$\text{Maximum Efficiency Loss} = \frac{9,790}{44,888 + 9,790} = 0.179 \quad (1)$$

The number of clients missing a specific number of appointments is graphed for the 4,478 clients in the study (see Figure 1). Remarkably, 1,646 clients, 37% of the 4,478 clients, had perfect attendance. How-

Table 1

Descriptive Statistics from Historical Data

| Variable	Number	Percentage
Age		
Client age group 16-64 inclusive	2840	40%
Client age group <16 and 65+	1638	60%
Total	4478	
Payment Source		
Client used private insurance or workers' compensation	3641	81%
Client used other payment method	837	19%
Total	4478	
Zip Code Match		
Client home zip code same as clinic zip code	1156	26%
Client home zip code different than clinic zip code	3322	74%
Total	4478	
Number of missed appointments	9790	18%
Number of kept appointments	44888	82%
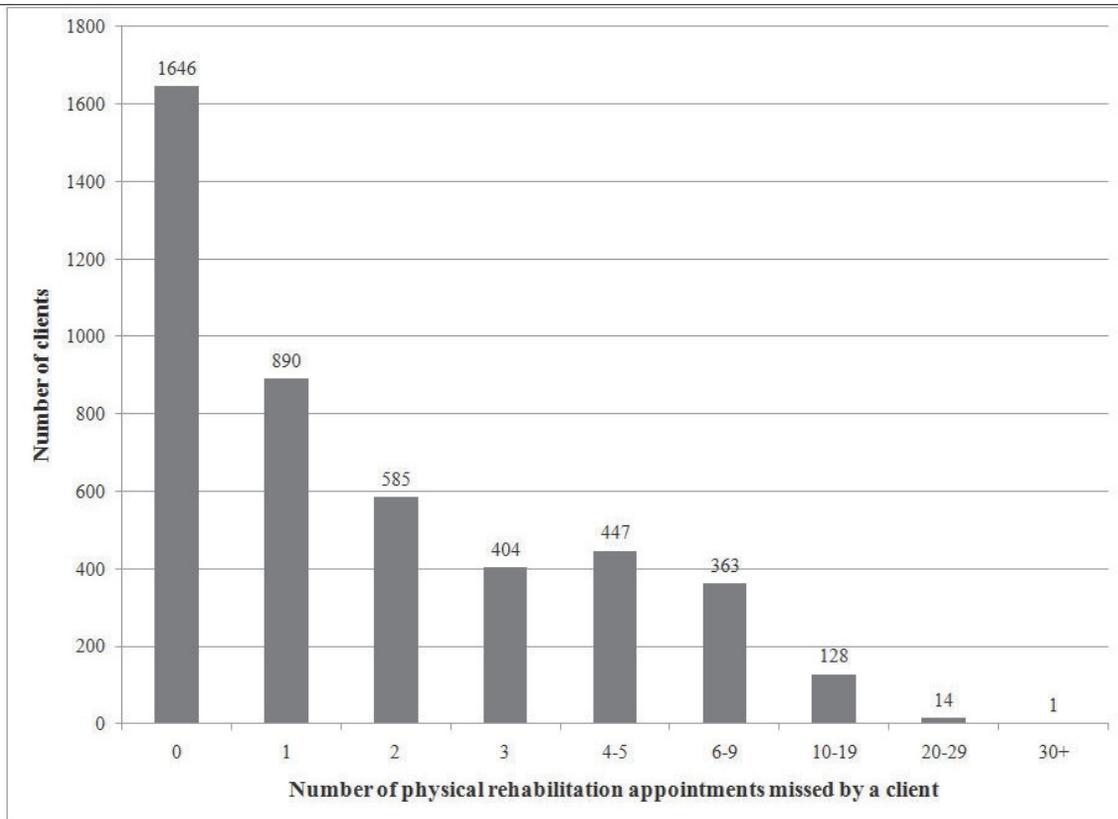
Figure 1. Number of clients missing a specific number of physical rehabilitation appointments (n=4,478)

Table 2
Intercorrelations of Study Variables

Variable Name	1	2	3	4	5
1 Age[a]	—-				
2 Payment Source[b]	-0.283[**]	—-			
3 Zip Code Match[c]	0.090[*]	-0.008	—-		
4 Number of Appointments Missed	-0.109[**]	-0.030	0.002	—-	
5 Kept Appointments	0.167[**]	0.015	0.035[*]	-0.608[**]	—-

Note. [a] Age is coded as 0 = less than 16 or greater than 65; 1 = 16 to 64, inclusive; [b] Payment source is coded as 0 = no private insurance or workers' compensation; 1 = private insurance or workers' compensation; [c] Zip code match is coded as 0 = clinic and client home have different zip codes; 1 = client home and clinic have same zip code; * $p < .05$; ** $p < .01$; n=3,582.

ever, an alarming 30% of clients missed three or more appointments.

Table 2 shows the intercorrelations among the study variables. The intercorrelations among the predictor variables are generally low, suggesting that multicollinearity does not pose a threat to the regression analysis. Correlations between the predictor variables with the outcome, percentage of kept appointments, are also generally low with the exception of the continuous predictor, the number of appointments missed.

Stepwise multiple regression analysis is presented for the percentage of kept appointments based on the independent dichotomous variables age group, payment method, zip code and the continuous variable, the number of appointments missed, in the developmental sample (see Table 3). All four of the variables included in the regression model, age, payment source, zip code match, and attendance history, were significant predictors of number of kept appointments. Individuals between the ages of 16 and 64 kept a lower number of scheduled appointments than those younger than 16 or older than 65. Given that age was used as a proxy variable for involvement in paid employment, this result supports the prediction in Hypothesis 1(a). With respect to Hypothesis 1(b), payment source was a significant predictor of percentage of kept appointments. As predicted, those with third-party payers are less likely to meet scheduled appointments. Zip code match was also a significant predictor of percentage of kept appointments. Clients with the same zip code as the clinic kept more appointments than individuals with a different zip code, thus supporting Hypothesis 1(c). Number of missed appointments is significantly and negatively

related to percentage of kept appointments. This finding supports Hypothesis 1(d).

The regression analysis in the developmental sample using all four predictor variables resulted in an R^2 value of .381. Cross validation of this regression model in the hold out sample revealed a cross-validated R^2 of .294. Thus, although the percentage of variance accounted for was reduced in cross-validation, the four predictors still accounted for a substantial amount of variance in the percentage of kept appointments.

Examination of the individual correlations of the predictor variables with the percentage of kept appointments suggested that by far the strongest individual predictor was the number of missed appointments. Using only that variable as a predictor resulted in an R^2 value of .370. The cross-validated R^2 value in the hold out sample was .277. If the set of three dichotomous variables was used to predict percentage of kept appointments, the resulting R^2 value was .032, with cross validation resulting in the same R^2 value, .032. Thus, it appears that most of the predictable variation in the percentage of kept appointments can be attributed to the number of missed appointments.

Discussion

The results indicate that the data currently contained in client charts can be used to identify clients likely to miss future appointments. The simple new model requires only four variables: age group, payment source, whether the client's home address zip code matches the clinic's zip code, and the number of scheduled appointments that have been missed. The R^2 value demonstrates that the independent variables

Table 3

Regression Analysis for Variables Predicting Percentage of Kept Appointments

Independent Variable	Coefficient	Standard Error
Intercept	0.875**	0.008
Age[a]	-0.048**	0.006
Payment source[b]	0.015*	0.008
Zip code match[c]	0.013*	0.006
Number of appointments missed	-0.041**	0.001

Note. [a] Age is coded as 0 = less than 16 or greater than 65; 1 = 16 to 64, inclusive; [b] Payment source is coded as 0 = no private insurance or workers' compensation; 1 = private insurance or workers' compensation; [c] Zip code match is coded as 0 = clinic and client home have different zip codes; 1 = client home and clinic have same zip code; * $p < .05$; ** $p < .01$; n = 3,582.

together explain 29% of the variability in client attendance, based on the cross-validation analysis conducted in the hold out sample.

Specifically, attendance history, represented by missed appointments, is negatively related to the percentage of appointments kept, indicating a greater propensity to miss future appointments after the first failure to appear for a scheduled appointment. This study suggests that attendance history is a helpful predictor of attendance, which is consistent with past studies (Collins et al., 2003; Lee et al., 2005; Starkenburg et al., 1988). For example, Starkenburg et al. (1988) found that the difference between early appointment keepers and no-shows was highly significant in predicting long-term appointment keeping. Likewise, Lee et al. (2005) also found that percentage of previous failed appointments was significant in predicting future appointment keeping. Similarly, Collins et al. (2003) found in their analysis that failure to attend appointments was one of two factors that was significant between a group of attenders versus a group of non-attenders. While this finding is not novel, it is important in that non-attendance is normally noted in the client record, and thus represents information easily available to the clinic personnel. Further, if such information is not normally recorded, it would require only a slight change in clinic procedures to make it available. The number of appointments missed remains a significant and strong predictor of percentage of appointments kept even in the absence of the other predictor variables, accounting for almost as much variance individually as the set of four predictors.

Age group was also a significant predictor of attendance. The group of clients between the ages of 16 and 64 were less likely to keep their appointments. This finding supported our hypothesis that meeting scheduled appointments might be more difficult for individuals who are engaged in full-time employment. Clients between the ages of 16 and 64 are most likely to have employment demands and family responsibilities to take up their time. Such individuals have to schedule their rehabilitation appointments around competing demands, with less success than would be desirable from the viewpoint of the rehabilitation clinic administrator.

Alternatively, one might speculate that transportation problems may impact physical rehabilitation clients in the age group 16 to 64 if their mobility has been temporarily impaired and they have trouble making transportation arrangements. For instance, clients in the age group 16 to 64 may find that an injury, post-surgery condition, or medication precludes their driving to appointments and requires them to find alternative means of transportation, a novel task for them.

It is interesting to note that while payment source is a statistically significant predictor of attendance, it demonstrates no significant relationship to the outcome as an individual predictor. We suggested that when a third party (especially one that is relatively "faceless") bears the expense, cost is less salient to the client, and thus the motivation to keep scheduled appointments would be lower. Our results were consistent with earlier studies that found a possible significant relationship between attendance and different payment sources (Davis et al., 1977; Grindley &

Zizzi, 2005). However, the absence of a bivariate relationship is also consistent with a finding that this predictor perhaps has less utility than the others (e.g., Kolt & McEvoy, 2003).

In the present study, zip code match served as a proxy variable for travel distance and performed as expected in the prediction model. This variable may serve as a proxy both for required travel distance and for the availability of public transportation. Those living outside of the zip code area of the clinic may also be outside of public transportation routes, eliminating one option for alternative travel arrangements. While one might wish for more valid measures of travel distance or availability of alternative travel options, client zip code is customarily collected by clinic personnel and match to the clinic's zip code is easily ascertained.

This analysis of the data raises important questions about client attendance prediction and subsequent intervention. Approximately 70% of the clients missed 0-2 appointments or 21% of the 9,790 missed appointments. By contrast, 30% of the clients missed 3 or more appointments or 79% of the 9,790 missed appointments. The results suggest to resource-constrained managers that early identification of the clients with lower kept appointment percentages could help them target costly intervention methods, such as extra appointment reminders or calls to clients to discuss concerns about transportation, client health, or treatment plan, where they are most needed to reduce efficiency loss. However, research is needed to determine which interventions are most effective to overcome non-attendance due to specific factors (Gatwood & Erickson, 2010).

Limitations
This study offers a simple, practical model of client non-attendance for physical rehabilitation, but several limitations can be identified. Each of these limitations presents an opportunity for future research to improve the simple model presented. One study indicates that client attendance for primary care is sensitive to particular clinics (Lasser, Mintzer, Lambert, Cabral, & Bor, 2005); however, the study presented here develops a prediction model from aggregated data from three clinic health systems with ten different facilities. A related issue is whether an attendance model developed for one specialty is applicable to other specialties. The simplicity of the prediction model presented here for physical rehabilitation will

facilitate validation and further model development for other clinic specialties.

The scarcity of data in some of the combined categories impacted the analysis. For example, there were no clients in the less than 16-year-old age group and very few clients in the 65-year-old and older age group with the workers' compensation payment source. Also, as indicated earlier, workers' compensation payment source was combined with the private insurance payment source for the statistical analysis due to a low number of individuals utilizing workers' compensation. The age groups were also combined to form two rather than three categories. Given that the present study is based on a relatively large sample size, it appears that certain category combinations may be extremely rare, which can present analytical problems for future research.

Implications and Future Research
Client charts frequently did not include information about whether the client missed a first appointment. It is possible that some clients missed their first appointment one or more times, but since most client charts are not formed until the client's first visit, the data for missing a first appointment was frequently not available. Given the importance of missed appointments as a predictor of future attendance, the absence of this information is problematic. Recording information about missed first appointments may be necessary in order to assist clinic personnel in predicting future attendance behavior. Some clinics combine specialties and even coordinate scheduling of client appointments sequentially for the different specialties (Demir, Chahed, Chaussalet, Toffa, & Fouladinajed, 2012). Thus, prediction of client attendance for multiple appointments raises yet another important research question.

Another critical set of research directions arises from the data not included in the prediction model. Other variables are needed to improve the assessment of client intention to attend. However, these new variables must be quick and easy to collect so that the cost of data collection does not exceed the value of the information. An important research question raised is what set of data pertaining to access could an appointment scheduling system or electronic medical record provide to better predict client behavioral intention to attend? For example, would the distance traveled from a client's residence, school, or workplace or the mobility of the client improve the model

enough to justify the collection of this type of access data?

In summary, results of the present study suggest that it is possible to develop a simple and usable model to predict client attendance for physical rehabilitation appointments. Furthermore, the data analyzed clearly demonstrate that client attendance behavior can substantially impact time utilized for client care and clinic efficiency.

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